Information, Decisions, and Productivity: On-Board Computers and Capacity Utilization in Trucking

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Productivity reflects not only how efficiently inputs are transformed into outputs, but also how well information is applied to resource allocation decisions. This paper examines how information technology has affected capacity utilization in the trucking industry. Estimates for 1997 indicate that advanced on-board computers (OBCs) have increased capacity utilization among adopting trucks by 13 percent. These increases are higher than for 1992, suggesting lags in the returns to adoption, and are highly skewed across hauls. The 1997 estimates imply that OBCs have enabled 3-percent higher capacity utilization in the industry, which translates to billions of dollars of annual benefits. (*JEL* D24, L92, O33, O47)

Theoretical links between economic performance and the use of information, such as those in F. A. Hayek's (1945) famous analysis of economic organization, are at the core of a recurring theme in the productivity literature: the premise that information technology (IT) offers opportunities for large productivity gains. Empirical evidence showing links between IT diffusion and productivity has been scarce until recently, however.[1] Researchers in the field refer to this as "the productivity paradox." The difficulty of finding relationships between IT use and productivity using aggregate data is well-summarized by Robert Solow's oft-cited observation: "You can see the computer age everywhere except in the productivity statistics."

This paper examines micro-level empirical relationships between IT use and productivity in the trucking industry in the 1990's. Productivity in this industry, as elsewhere in the economy, depends critically on how well information is brought to bear on resource allocation decisions.[2] Supply and demand conditions change constantly; forecasting exactly when and where trucks will be available and exactly when and where shippers will demand service is difficult more than a few hours in advance. Information about trucks' availability and value in different uses is highly dispersed, and communication costs create situations where the individuals deciding how individual trucks should be used—usually, dispatchers—do not have good information about trucks' availability. Trucks are not always allocated to their most valuable use as a consequence. Poor matches between capacity and demands lead to underutilization in the form of idle trucks and partially full or empty trailers.

Using truck-level data collected by the U.S. Bureau of the Census, I examine how on-board computer (OBC) use has affected capacity utilization. OBCs help managers at trucking firms or divisions monitor trucks and drivers. Low-end devices—trip recorders—make truck drivers' activities more contractible and help mechanics diagnose engine problems. High-end

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[1] Frank R. Lichtenberg (1995); Erik Brynjolffson and Lorin Hitt (1996); William Lehr and Lichtenberg (1998); Stephen D. Oliner and Daniel E. Sichel (2000); Dale W. Jorgenson (2001); Susan Athey and Scott Stern (2002). See Brynjolffson and Shinku Yang (1996) and Brynjolffson and Hitt (2000) for surveys of the evidence.

[2] That firms pay thousands of dollars for supply chain management software that provides managers up-to-date information about the status of production processes and inventories testifies that information about capacity is valuable and costly to obtain in other contexts.

devices—electronic vehicle management systems (EVMS)—also provide dispatchers real-time information about trucks' location and an efficient means of communicating with distant drivers. These additional capabilities let dispatchers make and implement better resource allocation decisions: they can allocate trucks across existing orders and market excess capacity better than they otherwise could. This, in turn, can lead to better matches between truck capacity and demands within and across firms. Better matches boost capacity utilization and productivity in the industry.

I find evidence that OBC use has increased capacity utilization significantly in the industry. Estimates using 1997 data indicate that loaded miles per period in use are 13 percent higher among trucks for which advanced OBCs have been adopted than those without OBCs. Other evidence suggests that this reflects that OBCs have caused capacity utilization increases by improving dispatchers' ability to make and implement resource allocation decisions. There is little evidence of truck utilization increases due to incentive improvements. The average benefits to adopters are higher in 1997 than 1992, suggesting lags in the returns to adoption, and are highly skewed across hauls. About three-quarters of the capacity utilization benefits are on trucks that haul goods long distances in nonspecialized trailers. The 1997 estimates imply that OBC-enabled improvements in decision-making have led to 3.3 percent higher capacity utilization in this nearly $500 billion sector of the economy, which translates to about $16 billion in annual benefits. These benefits are likely to increase as complementary economic institutions such as centralized markets develop in the industry and as diffusion becomes more widespread.

This study stands at the intersection of the productivity, economics of technology, and economics of organizations literatures, and is important for several reasons. First, it provides strong evidence of productivity gains from IT adoption. There is no "productivity paradox" in trucking. This study adds to a growing set of studies that document relationships between productivity and IT use, some of which are cited above. Relative to most other studies, the data and context studied here provide for an unusually good environment for measuring IT-related productivity gains. Second, as the Hayek cite indicates, understanding relationships between informational and resource allocation improvements is central for understanding the performance of economic organizations and how decreases in information costs lead to increases in welfare. This is one of the first empirical studies to examine these relationships in detail. An advantage of this paper's micro-level industry study approach [shared by Athey and Stern (2002)] is that one can understand exactly how and why IT use leads to productivity gains. Third, truck-tracking is one of the first commercially important wireless networking applications. Wireless networking applications are expected to diffuse more broadly in the economy in the near future; this study helps researchers understand their economic implications. The conclusion that OBCs have generated large benefits in trucking suggests that new networking applications have the potential to generate large welfare gains elsewhere.[3] Last, few individual applications have the potential for as significant a macroeconomic effect as OBC-enabled truck-tracking. OBCs fundamentally improved resource allocation decisions in an industry that interacts with most sectors of the economy and amounts to about 6 percent of GDP (including the value added produced by private fleets). OBC diffusion and related logistical improvements were nontrivial contributors to economic growth in the United States during the 1990's.

An outline of the rest of the paper follows. The next section describes the institutional setting and depicts how OBCs improve incentives and resource allocation decisions in trucking. Section II presents the data and the basic empirical patterns. Section III outlines the empirical framework. Section IV discusses the estimation results. Section V concludes.

I. Information and Capacity Utilization in Trucking

The physical part of the production process in trucking is simple. Cargo is loaded onto a truck, or a truck's trailer. An individual—a driver—drives the truck to its destination, where the

[3] See Robert J. Gordon (2000) for a skeptic's view.

cargo is unloaded. The output of the production process is the movement of cargo.

All else equal, costs per unit of output fall with capacity utilization. The per-unit cost of moving cargo on a truck increases less than proportionately with the weight of the cargo, and firms bear opportunity costs when trucks are idle, especially when idle trucks imply idle drivers. Truck capacity is lumpy and location- and time-specific. Capacity utilization is high when trucks haul a series of full loads, each of which starts close to and soon after the previous one finished.

Achieving high levels of capacity utilization is easy in some circumstances, but hard in others. When shippers have consistent demands to transport full loads of cargo back and forth between two points, high utilization rates can be achieved by dedicating trucks and drivers to a shipper and route. Most situations are not like this, however. Individual shippers usually do not have demands for both legs of a round trip and shipments often do not fill trailers. In such situations, high capacity utilization requires trucks to haul different shippers' cargo on the same run.

Capacity utilization thus depends largely on how well individuals can identify and agglomerate complementary demands onto individual trucks. Higher quality matches increase capacity utilization by keeping trucks on the road and loaded more, and therefore raise truck drivers' productivity.[4]

It follows that understanding the link between information and capacity utilization requires some understanding of the institutions that facilitate matching, individuals' role within these institutions, and how informational improvements lead to better matches both directly and through organizational changes. This is the topic of the next subsection.

A. *Institutions and Market Clearing*

Market clearing in trucking is unlike that in textbook economics models. It does not take place in centralized markets in which participants simply observe prices and decide how much capacity to sell to or buy from the market. Centralized markets have traditionally been unimportant in trucking, in large part because capacity and demands are highly differentiated in terms of time, location, and equipment characteristics. Organizing centralized markets that are so narrowly defined is costly relative to the benefits such markets would generate.[5] Instead, capacity and demand are matched in a highly decentralized manner in which buyers, sellers, and intermediaries engage in costly search. These parties identify trading opportunities by contacting each other directly rather than through markets.

One way complementary demands are identified is that shippers themselves search for other shippers with complementary demands. For example, a shipper with one-way demands between Chicago and St. Louis will search for a shipper with one-way demands between St. Louis and Chicago. However, much of the time complementary demands are identified by intermediaries, who add value by lowering search costs.

There are two main classes of intermediaries in trucking: for-hire carriers and brokers. They differ in whether they own trucks; for-hire carriers control truck fleets but brokers do not. As explained by George F. Baker and Hubbard (2003), truck ownership enhances intermediaries' incentives to find complementary hauls because it allows them to appropriate a greater share of the surplus. Most intermediaries in the industry are for-hire carriers. Shippers tend to use for-hire carriers when identifying complementary demands is important, such as for long or less-than-truckload hauls, and private fleets when it is not.

Shippers and carriers sometimes contract ahead for service. These contracts usually cover a series of recurring hauls. Arrangements of this sort reduce search costs by eliminating the need to search for trading partners recurrently, but tend to lower the short-term efficiency of the match between trucks and hauls.[6] Hubbard

[4] Links between productivity and the efficiency of the market-clearing process exist in many markets, particularly those like trucking in which supply and demand are highly differentiated. Labor markets are good examples.

[5] Narrowly defined markets tend to be illiquid, and matches in such markets may not improve much upon those achieved through decentralized matching.

[6] They may also serve to lower hold-up risks, by protecting relationship-specific informational investments. See Hubbard (2001).

(2001) shows that contracting becomes more prevalent relative to simple spot arrangements as local markets become thinner, particularly for long hauls. Shippers and carriers tend to rely on short-term arrangements when they use nonspecialized equipment for hauls on thick shipping lanes, but longer-term arrangements when they use specialized equipment or operate on thin shipping lanes. Capacity and demands tend to be matched over longer horizons for hauls involving specialized equipment than nonspecialized equipment.

Both the presence of intermediaries and the fact that most intermediaries own trucks thus can be interpreted as institutional responses to the matching problem. The presence of intermediaries lowers search costs; truck ownership provides intermediaries strong incentives to find good matches. These institutional features increase capacity utilization and thus raise truck drivers' productivity.

B. *Dispatch and Information*

Operationally, the people most directly involved in matching capacity to demand are dispatchers. Dispatchers assign trucks and drivers to hauls. Dispatchers who manage shippers' private fleets primarily assign trucks to their internal customer's hauls. Those who manage for-hire carriers' fleets assign trucks to external customers' (shippers') hauls. Dispatchers sometimes actively search for additional hauls when doing so would increase capacity utilization, contacting shippers either directly or through brokers.[7] For example, they try to find good "backhauls" (return trips).[8] Such activities are more common for dispatchers managing for-hire than private fleets. But they are not unusual within private fleets, particularly in cases where shippers use private fleets for long hauls.

Dispatchers work in a highly dynamic environment. Assignments and schedules are not set far in advance, particularly when it is hard to forecast exactly when individual shippers will demand service and exactly when particular trucks will come free. In practice, dispatchers assign trucks and drivers to a series of hauls at the beginning of the day or a shift. This is often a provisional schedule. They then update schedules throughout the day as situations warrant, rearranging assignments in response to unexpected delays and new service orders (some of which they may have actively solicited to fill capacity). Dispatchers who do this well increase the productivity of the trucks and drivers they manage.

Information is a critical input to dispatchers' decisions. In particular, knowing where trucks are and how full their trailers are lets dispatchers forecast better the time and location capacity will become available. Better forecasts, in turn, allow them to allocate trucks across existing orders and market spare capacity more efficiently. They also can provide customers better information about arrival times.

Information processing and communication capabilities are important as well, because they help dispatchers make good decisions and redirect drivers. Most dispatchers use route-planning software packages to help develop schedules. Many of these packages are relatively inexpensive and PC-based. Dispatchers commonly use the software to draft schedules, which they then revise to account for factors not accounted for by the software.

Communicating with drivers has traditionally been difficult when trucks operate outside radio range (about 25 miles). Dispatchers and drivers relied on a "check and call" system in which drivers stopped and called in every three to four hours. During the 1990's, declines in the price of long-distance cellular communication led many dispatchers and drivers to abandon this system and communicate with cellular phones. This has significant advantages over the previous system because it allows dispatchers to initiate contact with distant drivers just like they do with those close by. Dispatchers no longer have to wait until drivers call in to give them instructions, and drivers do not have to find a

[7] At larger firms, different individuals assign trucks to hauls and solicit business. I will abstract from the fact that individuals specialize, assuming that they work closely enough together so that they can be considered one decision-making unit.

[8] In principle dispatchers could also identify other hauls along the same route that would fill less-than-full trucks. In practice, trucks rarely pick up additional loads en route unless such loads are arranged well in advance. Many classes of cargo (especially bulk, liquid, or refrigerated cargo) cannot be mixed, and extra stops can increase the probability of late arrivals, especially when they are not planned in advance.

pay phone just to provide status reports and ask if there are schedule changes. Using cell phones alone has drawbacks, however. In particular, there remain significant coverage gaps, and information about trucks' location takes time to collect and is neither verifiable nor in electronically processable form.

Thus, information costs have traditionally lowered capacity utilization in the industry because difficulties in monitoring trucks' location and communicating schedule changes to drivers have made it hard for dispatchers to match trucks to hauls efficiently while trucks are on the road. This has been particularly the case when trucks operate far from home and demands are not regular. Finding complementary "backhauls" is particularly important and communicating with drivers sometimes difficult when hauls take trucks far from their base and irregularity makes it hard to arrange for backhauls in advance.

C. *On-Board Computers*

Two classes of OBCs began to diffuse in the trucking industry in the late 1980's: trip recorders and electronic vehicle management systems (EVMS).

Trip recorders monitor how drivers operate trucks. They record when trucks were turned on and off, trucks' speed over time, and incidents of hard braking. Trip recorders collect data onto a storage device. Dispatchers upload these data once drivers return to their base. The data trip recorders collect provide dispatchers verifiable information regarding drivers' activities, including whether they were speeding or took unauthorized breaks. Trip recorders also track how trucks' engines perform; for example, they track fault codes that result when engines work improperly. This information is useful to mechanics because it helps them diagnose engine problems better.

Trip recorders are thus useful for improving drivers' incentives and mechanics' maintenance decisions. They are not particularly useful for improving dispatchers' resource allocation decisions because they do not provide dispatchers information in a timely enough fashion.

EVMS are more advanced than trip recorders. They contain all trip recorders' capabilities. In addition, they record trucks' geographic location (for example, using satellite tracking) and provide a close-to-real-time data connection between dispatchers and trucks. These additional capabilities help dispatchers make better scheduling decisions and communicate them quickly to drivers. Knowing exactly where trucks are helps dispatchers allocate trucks across existing service orders and market excess capacity better. The communication link helps them notify drivers of schedule changes quickly and effectively. From above, one would expect these capabilities to be particularly important when trucks haul goods long distances on irregular schedules, since monitoring and communication costs traditionally have had a large impact on dispatchers' ability to match trucks to hauls efficiently in such situations.

The ways in which OBCs affect supply in trucking guide the empirical strategy. Conceptually, capacity utilization reflects both loaded miles during the periods that trucks are "in use," (i.e., away from their base) and the number of periods trucks are in use. From the discussion above, improvements in drivers' incentives and dispatchers' resource allocation decisions primarily affect supply by increasing loaded miles during the periods trucks are in use, for example by reducing the time during a run that trucks are idle or run empty. Because this is the margin where truck-level relationships between OBC use and capacity utilization are most likely to reflect their effect on supply, this paper seeks to estimate how much OBCs affect loaded miles per period in use.

In contrast, truck-level relationships between OBC use and periods in use are unlikely to reflect OBCs' effect on supply: monitoring improvements generally do not affect how many periods trucks can potentially be "in use."[9] Such relationships instead are likely to reflect the

[9] There may be exceptions to this, though I do not believe these exceptions to be significant empirically. Consider a situation when scheduling a truck for an out-and-back run would lead it to be idle the following period when it is at its base. If EVMS newly leads dispatchers to find hauls that would bring it back in a "triangle," thus avoiding an idle period at home, this would increase periods in use but not loaded miles per period in use. I believe such an effect to be minor; whether trucks are scheduled on "out-and-back" or more complicated routes depends far more on the size of demands in different shipping lanes than dispatchers' ability to match trucks more precisely to these demands.

allocation of demand across trucks—they would exist if shippers shift demands toward trucking firms whose trucks have OBCs and away from those whose trucks do not, or if dispatchers utilize their best-equipped trucks more than other trucks when capacity exceeds demand—and might appear even if OBCs had no supply-side effect on capacity utilization. Alternatively, such relationships may reflect reverse causation: truck owners may adopt OBCs more when they expect trucks to be used more periods. An important goal of the empirical framework will be to disentangle relationships between OBC use and loaded miles per period in use from those between OBC use and periods in use. However, this will involve controlling for rather than interpreting relationships between OBC use and periods in use.[10]

There is an important economic distinction between trip recorders and EVMS. Both classes of devices are useful for improving incentives and maintenance decisions. EVMS, however, are also useful for improving resource allocation decisions ("coordination").

This paper focuses primarily on the impact of OBCs' coordination-improving capabilities on capacity utilization.[11] There are two reasons for this.

First, evidence from the trade press and plant visits indicates that OBCs primarily affect supply through better dispatch, not through improvements in drivers' incentives or maintenance decisions. One exception to this is when drivers' jobs involve cargo handling as well as driving; some firms attribute productivity gains to the ability to track how long drivers spend at stops. Trucks can be utilized more intensively when drivers load and unload cargo faster (see Baker and Hubbard, 2003). OBC adoption also may have led some firms to provide drivers stronger fuel economy-based incentives, and this may have led to productivity gains, but there is little indication that these increases are substantial.

Second, it is difficult to isolate the impact of OBCs' incentive-improving capabilities, because all OBCs have both incentive- and maintenance-improving capabilities.

II. Data

The data are from the U.S. Bureau of the Census' 1992 and 1997 *Truck Inventory and Use Surveys* (TIUS).[12] The TIUS is a mail-out survey taken every five years as part of the Census of Transportation. The Census takes a random sample of trucks from vehicle registration records, and sends their owners a questionnaire that asks them about the characteristics and use of their trucks.[13] For example, questions ask respondents their trucks' make and model. Importantly for this study, the Survey asks whether trucks have trip recorders or EVMS installed. It also asks many questions about how trucks were used during the previous year, including such things as whether they were owned by their driver, whether they operated within a private or for-hire fleet, how far from home they generally operated, what kind of trailer was attached, what classes of products they carried, and the state in which they were based. Although the TIUS contains observations of a wide variety of truck types, all of the analysis in this paper uses only observations of truck-tractors, the front halves of tractor-trailer combinations.

The Survey also asks several questions that elicit information regarding how intensively individual trucks were utilized. Answers to these questions provide the variables used to evaluate productivity. One question asks how many miles the truck was driven during the previous year. Other questions ask what fraction of miles the truck was driven without a trailer, and what fraction of miles it was driven empty. Combined

[10] To the extent that relationships between OBC use and periods in use *do* reflect that OBCs increase periods in use, focusing only on how OBCs affect loaded miles per period in use would understate how much OBCs affect capacity utilization.

[11] Other papers [Baker and Hubbard (2000, 2003)] have examined the organizational implications of OBCs' incentive-improving capabilities.

[12] The 1997 Survey is actually called the Vehicle Inventory and Use Survey. See U.S. Bureau of the Census (1995, 2000) and Hubbard (2000) for more details about these Surveys.

[13] Since draws are taken from vehicle identification numbers, sampling is randomized across trucks, not firms or industry sectors. The trucks in my 1992 sample make up about 3 percent of truck-tractors registered in the United States; sampling rates were about one-third lower in 1997 than 1992 for budgetary reasons.

with the number of miles the truck was driven, answers to these questions indicate the number of miles the truck was driven with cargo ("loaded miles"). The Survey also asks the weight of the truck when empty and the average weight of the truck plus cargo during a typical haul in the previous year. The difference between these figures is the average weight of the cargo the truck hauled ("cargo weight"). Multiplying loaded miles by cargo weight and dividing by 2,000 gives an estimate of the truck's output during the previous year in ton-miles. Finally, the Survey asks owners how many weeks out of the year trucks were in use, defined as the number of weeks in which a truck is ever used to haul cargo. As I discuss below, this is an important variable in the analysis. Its absence from previous Surveys is the reason I use only the 1992 and 1997 Surveys.

Responses to these questions likely overstate trucks' output and capacity utilization somewhat, although probably in a similar fashion from year to year. Cargo weight is probably overstated because respondents likely report cargo weight when trucks leave terminals, which is not the average amount of cargo in trucks' trailers while loaded when trucks deliver to multiple points.[14] Respondents likely understate empty miles, particularly when trucks haul trailers for which backhauls are unlikely such as auto trailers. This is because respondents who do not try to find backhauls may not include backhaul capacity in the denominator of this fraction. But this bias works against finding relationships between OBC adoption and capacity utilization increases if adoption leads firms to reconsider what they think of as unused capacity: for example, if it leads them to newly consider empty backhauls as empty miles.

The Survey therefore provides detailed information about production at the individual truck level. This level of disaggregation is rare, and provides a significant advantage in studying technology adoption, organizational structure, and productivity issues.[15] The Survey does not, however, allow one to identify trucks' owners. It is therefore impossible to determine the for-hire or private fleet in which individual trucks operated. Although one can aggregate up to the industry or industry-segment level, the data cannot be used to investigate productivity at the firm level.

Finally, it is important to recognize that the TIUS does not collect panel data; rather, it is a series of repeated cross sections. One does not observe exactly the same trucks or hauls from year to year. This limits the extent to which I can exploit the data's time dimension. I have explored doing so in a way analogous to my other work (Baker and Hubbard, 2000, 2003): aggregating the data up to narrowly defined market segments (for example, state-product class-trailer type-distance combinations) in each year, and relating segment-level changes in OBC use to segment-level changes in average loaded miles per period. But cross-sectional patterns in the data indicated that this method was very likely to produce biased estimates of the true relationships between OBC use and capacity utilization. I estimated cross-sectional relationships between OBC use and loaded miles per period at the segment and truck level and found that the segment-level relationships were much stronger.[16] Because the segment-level relationships do not track the micro-level relationships in the cross section, I concluded that they were unlikely to do so in the time series, and in fact were likely to bias estimates of OBCs' effect on capacity utilization upward.

The following subsection introduces the data and shows some broad patterns that indicate relationships between changes in capacity utilization measures and changes in OBC use between 1992 and 1997. However, the main

[14] Aggregate mileage estimates for the entire U.S. trucking fleet from the TIUS are consistent with those from other sources, but ton-mile estimates are not. This indicates that the cargo weight data in the TIUS are not very reliable. I therefore use loaded miles rather than ton-miles as my main output measure in the analysis below.

[15] The manufacturing equivalent perhaps would be to have data at the level of the production line rather than the establishment or firm.

[16] The specifications are analogous to those reported in the first column of Table 3, and include controls for distance, trailer type, and other haul characteristics. The segment-level point estimates using the 1997 data suggest that trip recorder adoption raises loaded miles per period by 20–25 percent, depending on how narrowly segments are defined; in contrast, the truck-level estimates presented below suggest that it raises loaded miles per period by 2 percent.

TABLE 1—TRUCK UTILIZATION AND OBC USE—1992, 1997

	Miles	Loaded miles	Fraction w/load	Cargo weight	Ton-miles	Trip recorder	EVMS	N
Panel A: All Trucks								
1992	65,451	58,559	0.882	38,190	1,178	0.078	0.111	36,082
1997	70,351	64,500	0.904	39,223	1,325	0.084	0.249	23,183
Change (percent)	7.49	10.15	2.49	2.70	12.48	7.69	124.32	
Panel B: Trucks in Use > 48 Weeks								
1992	77,764	69,993	0.893	37,890	1,399	0.100	0.152	18,683
1997	82,488	75,836	0.915	39,602	1,592	0.093	0.301	11,376
Change (percent)	6.07	8.35	2.46	4.52	13.80	−7.00	98.03	

Notes: Miles is the average number of miles trucks were operated. Loaded miles is the average number of miles trucks were operated and loaded. Fraction with load is loaded miles/miles, averaged across trucks. Cargo weight is the average weight of the cargo trucks hauled when loaded. Ton-miles is cargo weight multiplied by loaded miles, averaged across trucks. Trip recorder is the share of trucks with a trip recorder installed. EVMS is the share of trucks with an EVMS installed.

empirical evidence in this paper will exploit cross-sectional rather than time variation in the data.

A. *Simple Patterns*

Table 1 presents simple trends. The top panel indicates that capacity utilization increased between 1992 and 1997. On average, miles per truck increased by 7.5 percent and loaded miles increased by 10.1 percent. Although the cargo weight data in the TIUS are not very reliable, there is no indication that average cargo weight decreased during this time. Reports from these data indicate that it increased by 2.5 percent, leading to a 12.5 percent increase in ton-miles per truck. OBC use increased during this period as well. The fraction of trucks with a trip recorder installed increased slightly from 7.8 percent to 8.4 percent, while the fraction with an EVMS installed more than doubled from 11.1 percent to 24.9 percent.

The bottom panel reports similar figures, averaging only over trucks that were in use at least 48 weeks out of the year. Comparing trends in these figures to those in the top panel provides some evidence regarding the extent to which increases in capacity utilization were due to increases in the number of periods in use rather than increases in how intensively trucks were used conditional on periods in use. Loaded miles increased by 8.3 percent within this subsample—somewhat less than the 10.1 percent increase within the full sample, but still a large increase. These figures do not suggest that increases in capacity utilization during this period were entirely due to the fact that trucks were used more weeks out of the year in 1997 than 1992. Capacity utilization increased during this time even among the most intensively used trucks. OBC use was high for these trucks as well.

Figure 1 provides further evidence. This plots average weeks in use, by truck age, for the 1992 and 1997 samples. If increases in loaded miles reflect increases in the utilization of infrequently used trucks, older trucks should be used more weeks in 1997 than 1992. Figure 1 indicates that while weeks in use declines steadily with truck age in both years, the plots track each other very closely.[17] There is no evidence that older trucks were used more weeks per year in 1997 than 1992.

Figure 2 relates loaded miles per week in use to net EVMS adoption. The lines plot loaded miles per week in use as a function of age; the bars report the share of n-year-old trucks with EVMS in 1997, less the share of n-year-old trucks with EVMS in 1992. There are three important facts. First, old trucks are used less intensively than new ones, even conditional on weeks in use. Second, the gap between 1997 and 1992 trucks is greater when comparing new trucks than old trucks. Once again the greatest

[17] The low figure for brand-new trucks reflects that many were put into service in the middle of the survey year.

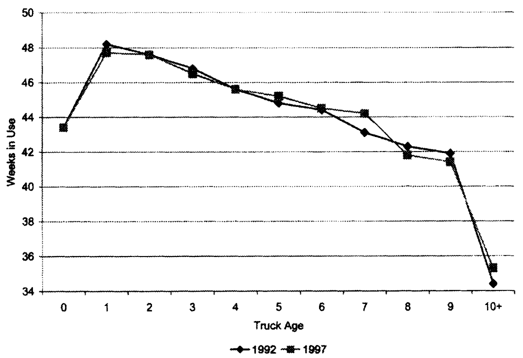

FIGURE 1. AVERAGE WEEKS IN USE

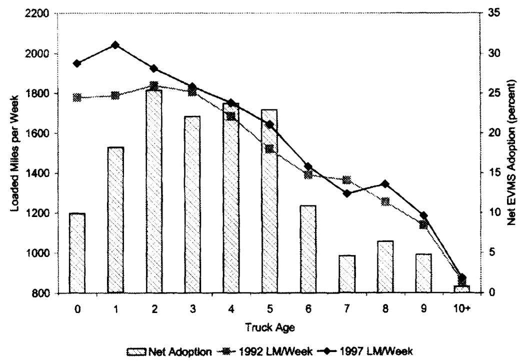

FIGURE 2. LOADED MILES PER WEEK, NET EVMS ADOPTION

increase in capacity utilization is for the trucks that are already utilized intensively. Third, the gap between the 1997 and 1992 trucks is widest where net adoption is highest—for one- to five-year-old trucks. 1992–1996 model year trucks had much higher EVMS use rates in 1997 than 1987–1991 model year trucks did in 1992. Capacity utilization rates also appear to increase more for trucks in this range than younger or older trucks.

Combined, these tables provide evidence consistent with the hypothesis that EVMS adoption contributed to increases in capacity utilization. Capacity utilization increased the most for already intensively used trucks, and trucks for which EVMS tended to be adopted most had the greatest increases in capacity utilization.

Furthermore, additional evidence indicates that capacity utilization increases during this time also represent increases in labor productivity. Increases in loaded miles per truck would *not* reflect increases in labor productivity if the ratio between drivers and trucks changed, as would be the case if firms were using trucks (but not drivers) for double shifts more in 1997 than 1992. However, data from the October CPS indicates that the number of truck drivers increased by 26.8 percent between 1992 and 1997; the 1997 VIUS indicates that the number of heavy duty trucks increased by 25.7 percent. While this evidence is not necessarily conclusive, since the CPS does not distinguish between drivers of heavy- and lighter-duty trucks, these figures do not indicate that there were any important changes in the driver-truck ratio during this time.

B. *Periods and Weeks*

As noted above, the goal of this paper is to estimate how much OBCs have increased loaded miles per period in use. An empirical problem arises because while one would like information on the number of periods (e.g., hours or shifts) trucks are in use, the data instead contain information on the number of weeks trucks are in use. If the relationship between periods in use and weeks in use were one-to-one, the difference between weeks and periods in use would just be a difference in units and normalizing loaded miles by weeks in use would amount to the same thing as normalizing by periods in use. But this need not be the case because trucks are counted as "in use" during a week regardless of whether they are used for one or many shifts. In fact, an increase in the number of periods could result in no change in the number of weeks, for example if it were accomplished by utilizing trucks for more shifts during the weeks they were already used.

Although a zero elasticity between periods in use and weeks in use would be an extreme case, the example illuminates a general point: the relationship between periods in use and weeks in use is unknown, and one must estimate it in order to utilize information on weeks in use to control for periods in use. If part of what happens as periods in use increase is that trucks are used for more periods during weeks they are already in use, differences in weeks in use would understate differences in periods in use, and simply normalizing loaded miles by weeks in use would not completely correct for differences in periods in use.

One of the patterns in Figure 2 manifests this. All else equal, loaded miles per period in use should not vary across vintages: conditional on being in use during a period, old trucks can be used about as intensively as new ones. Thus, the fact that loaded miles per week is considerably lower for old trucks than new ones implies that simply normalizing loaded miles by how many weeks trucks are in use does not completely control for differences in how many periods trucks are in use.[18] Much of the next section focuses on developing a more sophisticated way to utilize data on weeks in use to control for differences in periods in use.

III. Empirical Framework

Let y_{it} equal loaded miles for truck i in period t, where period corresponds to a day or shift. Let k_{it} be a dummy variable that equals one if truck i is in use in period t and zero otherwise. Since $y_{it} = 0$ during periods truck i is not in use, one can write y_i^1, truck i's loaded miles over the course of T periods, as:

$$y_i^1 = \sum_{t=1}^{T} y_{it} k_{it}. \tag{1}$$

Assume for simplicity that loaded miles per period in use for truck i is constant across periods: trucks are used in similar ways from period to period, conditional on being in use.[19] Let s_i equal the share of periods that truck i is in use. Then one can rewrite y_i^1 as:

$$y_i^1 = y_i s_i T \tag{2}$$

where y_i is loaded miles for truck i per period in use.

y_i is influenced by many factors, including the characteristics of the hauls for which the truck is used, the characteristics of the firm finding hauls for the truck, and the informational environment. Haul characteristics matter because they affect how much time trucks spend at stops being loaded and unloaded and how fast they travel when moving; for example, y_i tends to be higher for trucks used for long than short hauls because such trucks spend less time at loading docks or on congested city streets. Firm characteristics matter if some firms have better information about demand than others and this lets them find better backhauls for the truck. Whether trucks have OBCs affects the informational environment, and can affect y_i by improving drivers' incentives or by improving dispatchers' knowledge and communication capabilities. The latter may facilitate better matches between trucks and hauls. I specify $\ln y_i$ as:

$$\ln y_i = \mathbf{X}_i\boldsymbol{\beta} + \boldsymbol{\delta}_1\mathbf{D}_i + \varepsilon_{1i} \tag{3}$$

where $\mathbf{X}_i$ includes observable haul and firm characteristics that affect loaded miles per period in use and $\mathbf{D}_i$ is a vector of dummies that reflect whether and what kind of OBCs are installed on the truck. ε_{1i} captures the effect of unobserved haul and firm characteristics. To simplify exposition, assume for now that $\boldsymbol{\delta}_1$ does not vary.

I next discuss s_i. I assume that s_i is related to demand, truck, and firm characteristics by the following reduced-form equation.

$$\ln s_i = \mathbf{Z}_i\boldsymbol{\gamma} + \boldsymbol{\delta}_2\mathbf{D}_i + \varepsilon_{2i}. \tag{4}$$

$\mathbf{Z}_i$ includes observable variables that are correlated with the share of periods trucks are in use. These may include variables that are also in $\mathbf{X}_i$. One variable that I will assume to be part of $\mathbf{Z}_i$ but not $\mathbf{X}_i$ is truck age: trucks' age may be correlated with the share of periods they are used (perhaps because dispatchers put their newest trucks in use when capacity exceeds demand) but does not affect how intensively they can be used, given that they are in use during a period.[20] $\mathbf{D}_i$ is as above. $\boldsymbol{\delta}_2$ captures

[18] Although Figure 2 shows unconditional differences, these differences remain economically and statistically significant when including controls for how trucks are used.

[19] There is some evidence on this in the data. For example, the Survey asks owners to report individual trucks' share of miles by haul length, product class, and governance form. Though the quality of the share data may not be good, these data strongly suggest that most trucks are used in consistent ways from period to period.

[20] This restriction produces conservative estimates of OBCs' effect on loaded miles per period in use; see below.

correlations between OBC use and the share of periods truck i is in use. As described above, such correlations could arise for several reasons. OBC use may lead the share of periods to be higher because shippers may reallocate demand toward trucking firms with OBC-equipped trucks, or dispatchers may put OBC-equipped trucks in service and idle others when capacity exceeds demand. Alternatively, correlations may arise because of reverse causation: OBCs are more valuable when trucks are in use more. ε_{2i} is a residual, and represents relationships between s_i and unobserved factors that are orthogonal to both $\mathbf{Z}_i$ and $\mathbf{D}_i$. Since this is a reduced form, by construction, $E(\varepsilon_{2i}|\mathbf{Z}_i, \mathbf{D}_i) = 0$.

Taking logs of equation (2) and substituting in equations (3) and (4), I obtain:

(5)

$$\ln y_i^1 = \mathbf{X}_i\boldsymbol{\beta} + \mathbf{Z}_i\boldsymbol{\gamma} + (\boldsymbol{\delta}_1 + \boldsymbol{\delta}_2)\mathbf{D}_i + \varepsilon_{1i} + \varepsilon_{2i}.$$

This equation relates loaded miles to OBC use.[21] The empirical goal is to estimate OBCs' effect on loaded miles per period in use, $\boldsymbol{\delta}_1$. However, as this equation shows, even if the orthogonality condition $E(\varepsilon_{1i}|\mathbf{D}_i) = 0$ holds, least-squares estimates of loaded miles on OBC use reflect both OBCs' effect on capacity utilization and correlations between OBC use and the share of periods trucks are in use. I next discuss a method to estimate $\boldsymbol{\delta}_1$ separately from $\boldsymbol{\delta}_2$ that exploits the fact that the data contain information on the share of weeks trucks are in use. A key step in this method is identifying $\partial \ln y_i^2/\partial \ln s_i$, the elasticity between weeks in use and periods in use. Thereafter I discuss the orthogonality condition, and interpretations of the estimates when OBCs' effect on y_i differs across hauls.

Let y_i^2 equal the share of weeks truck i is in use over the course of T periods, and specify:

$$y_i^2 = s_i^\lambda h_i. \tag{6}$$

λ is the elasticity between the share of weeks in use and the share of periods in use. If $0 < \lambda < 1$, the relationship between y_i^2 and s_i is concave; trucks that are used a higher fraction of periods are used more weeks per year, but at a decreasing rate.[22] h_i includes factors that affect the number of weeks in use, conditional on the number of periods in use. h_i would be higher when demands for the truck are more cyclical: for example, trucks that primarily haul agricultural goods tend to be used a low number of weeks relative to periods because demand comes in spurts. Assuming that $\ln h_i = \mathbf{W}_i\boldsymbol{\alpha} + \varepsilon_{3i}$, I therefore have the following:

(7)

$$\ln y_i^1 = \mathbf{X}_i\boldsymbol{\beta} + \mathbf{Z}_i\boldsymbol{\gamma} + (\boldsymbol{\delta}_1 + \boldsymbol{\delta}_2)\mathbf{D}_i + \varepsilon_{1i} + \varepsilon_{2i}$$

$$\ln y_i^2 = \mathbf{W}_i\boldsymbol{\alpha} + \lambda\mathbf{Z}_i\boldsymbol{\gamma} + \lambda\boldsymbol{\delta}_2\mathbf{D}_i + \varepsilon_{3i} + \lambda\varepsilon_{2i}.$$

$\boldsymbol{\delta}_1$ and $\boldsymbol{\delta}_2$ are now separately identified. The logic is that if trucks with OBCs are used more weeks than those without them, this should reflect differences in the number of periods trucks with and without OBCs are used. One can thus use the relationship between weeks in use and OBC use to back out how much relationships between loaded miles and OBC use reflect differences in loaded miles per period in use. Doing so is simple if $\lambda = 1$: subtracting the second equation from the first differences out $\boldsymbol{\delta}_2\mathbf{D}_i$. But as the discussion above emphasizes, unitary elasticity between periods and weeks in use is unlikely; one must instead estimate λ. This requires having at least one variable that is related to the share of periods trucks operate but does not affect loaded miles per period. I assume this to be the case for truck vintage, and estimate λ from the ratio of the relationships between vintage and the two dependent variables.[23]

My identification strategy implies the follow-

[21] To simplify the exposition, I have dropped the term $\ln T$ from the right-hand side of this equation. This is without loss of generality, since $\ln T$ is not separately identified from β_0, the constant term in the vector $\boldsymbol{\beta}$.

[22] Concavity would be an important property of more structurally derived expressions of the relationship between periods and weeks in use. The reduced-form specification used here captures this feature in a parsimonious way, and produces a straightforward set of estimating equations from which it is clear how each of the parameters is identified by the data. I discuss identification further below.

[23] Although the estimation procedure below allows the error terms in the two equations to covary, this covariance does not help me identify λ unless I were to put further restrictions on the variance of ε_1, ε_2, or ε_3.

ing. Suppose trucks differ only in their vintage and whether they have OBCs. Suppose young trucks are used 10 percent more weeks, but have 20 percent more loaded miles, than old ones. Suppose trucks with OBCs are used 10 percent more weeks than those without them, but have 25 percent more loaded miles. Then $\lambda\gamma = 0.1$, $\gamma = 0.2$, $\lambda\delta_2 = 0.1$, and $\delta_1 + \delta_2 = 0.25$. Solving for δ_1, the estimates would indicate that trucks with OBCs have 5 percent higher loaded miles per period in use than those without them.

An important identifying assumption is that correlations between truck vintage and loaded miles reflect only differences in the number of periods in use, not differences in loaded miles per period in use. This assumption tends to produce conservative estimates of the relationship between OBC use and loaded miles per period in use: if new trucks can be used more miles per period than old trucks, my estimate of δ_1 would be downward biased. To see this, consider the example above, but suppose new trucks can be used 5 percent more miles per period than old trucks. If they have 20 percent more loaded miles, this implies that they are used 15 percent, not 20 percent, more periods than old trucks: the true value of γ is 0.15, not 0.20. The equations $\lambda\gamma = 0.1$, $\lambda\delta_2 = 0.1$, and $\delta_1 + \delta_2 = 0.25$ would then imply that the true values of the rest of parameters are $\lambda = 0.67$, $\delta_2 = 0.15$, and $\delta_1 = 0.10$. My estimate of δ_1 would indicate that loaded miles per period in use was 5 percent higher for trucks with OBCs than those without them when it was really 10 percent higher.

A. *Causality*

Interpreting δ_1 as OBCs' impact on loaded miles per period in use requires the orthogonality condition $E(\varepsilon_{1i}|\mathbf{D}_i) = 0$ to hold: OBC use is independent of unobserved haul and firm characteristics that affect loaded miles per period in use. Note that the relevant issue *does not* concern whether adoption is higher when trucks are used more periods—this is a reason why normalizing loaded miles by periods in use is important. If within firms, OBCs are installed on trucks that are expected to be used heavily, or if firms that are able to keep trucks out on the road more of the time also adopt OBCs more, this is picked up by δ_2.[24] The relevant issue is narrower. It concerns whether biases arise because adoption is greater on trucks that, absent OBCs, would accumulate more loaded miles during the periods they spend out on the road.

Unobserved haul characteristics in ε_{1i} include factors that affect how much time trucks spend at loading docks and their speed while on the move, conditional on $\mathbf{X}_i$.

One potential violation of the orthogonality condition arises because drivers' jobs differ across hauls in unobserved ways, and this could both drive differences in the time trucks spend at loading docks and the extent to which different classes of OBCs are used. Baker and Hubbard (2003) report that hauls differ in whether drivers have nondriving service responsibilities such as sorting and shelving cargo upon delivery. Loaded miles per period in use tend to be lower when drivers have such responsibilities because stops take longer: drivers do not merely drop off cargo and leave. Furthermore, the returns to adoption may differ with this unobserved haul characteristic. OBCs' incentive-improving capabilities would be more valuable if monitoring's benefits are greater in multitasking environments; their coordination-improving capabilities would be less valuable if giving drivers service responsibilities interferes with dispatchers' ability to identify and implement good matches by making it more difficult for dispatchers to forecast when trucks will come free, even when they know where trucks are. If so, one would expect trip recorder adoption to be high, and EVMS adoption to be low relative to trip recorder adoption, in circumstances where loaded miles per period is low because of unobserved service. This would bias estimates of trip recorders' effect downward and EVMS' effect relative to trip recorders' upward.

[24] However, it turns out that firm effects such as this probably are not empirically important once one controls for truck age and haul characteristics. The estimates of δ_2 below will *not* show that trucks with advanced OBCs are used more periods than trucks without OBCs. This suggests that unobserved firm characteristics that broadly affect truck utilization are not strongly correlated with EVMS adoption, and is a reason I focus more below on problems associated with unobserved haul than firm characteristics.

I investigate the extent to which unobserved service responsibilities are biasing the results in the following way. Drivers' responsibilities differ systematically between private and for-hire carriage; on average, they have much greater service responsibilities within private fleets.[25] If unobserved differences in drivers' responsibilities bias estimates of OBCs' impact on loaded miles per period in use, one would expect that omitting the private fleet dummy would do so as well. Finding instead that $\boldsymbol{\delta}_1$ does not change when excluding the private fleet dummy is evidence that the bias due to unobserved service differences is likely small.

Another possibility also concerns unobserved differences in time spent picking up and delivering cargo. Shippers and receivers differ in the sophistication with which they handle goods, and this is not directly observed in the data. Suppose some receivers of goods have better logistics practices than others, and sophisticated receivers are both able to unload trucks faster because of better handling methods and value using carriers with OBC-equipped trucks.[26] This would induce a spurious correlation between loaded miles per period in use and OBC use, even if OBCs did not cause loaded miles per period in use to increase. I examine this possibility in the following manner. Receivers' organizational sophistication varies with the products they receive—it tends to be higher for product classes that are delivered to manufacturers or warehouse facilities than those delivered to raw input processors or retail outlets. I therefore examine whether the coefficients change when including a set of dummy variables that control for the products trucks generally haul; finding that they do not suggests that relationships between OBC use and loaded miles per period in use do not reflect spurious correlations due to unobserved differences in logistical sophistication.

[25] Industry publications commonly remark on this; for example Standard and Poor's (1995) states that using private fleets is valuable because of "overall superior service to customers." Baker and Hubbard (2003) propose that shippers' make-or-buy decision is complementary to decisions regarding whether drivers have service responsibilities, and find evidence in favor of this proposition.

[26] Hubbard (2000) provides evidence that OBC use is greater on trucks that haul products with high sales-inventory ratios than low ones, suggesting that logistical sophistication and OBC use are related.

Unobserved haul characteristics also include factors that affect trucks' speed while on the road. Thus, another reason that the orthogonality condition might not hold is that both loaded miles per period in use and OBC adoption may be greater when trucks operate in less congested areas. Loaded miles per period in use might be greater because of fewer traffic problems; EVMS adoption might be greater because satellite-based communication links are more valuable when cell phone coverage is spottier and pay phones scarcer. Once again, I investigate this through a sort of robustness check. Congestion varies substantially geographically: greater in the East than the West, for example. If there are spurious correlation problems related to cross-sectional differences in congestion, estimates of $\boldsymbol{\delta}_1$ should change when I include additional controls for where trucks are based. I explore this by comparing the coefficients when including and excluding dummies that indicate the state in which trucks are based from $\mathbf{X}_i$. Finding that $\boldsymbol{\delta}_1$ is robust to whether state dummies are included is evidence that any biases induced by such spurious correlations are probably small.

ε_{1i} also includes unobserved firm characteristics. These reflect, for example, how well the truck's owner (or an intermediary the owner uses) can find backhauls for the truck absent OBCs, holding constant the owner's ability to keep trucks "in use." Such factors would cause $E(\varepsilon_{1i}|\mathbf{D}_i) = 0$ to fail under circumstances such as the following. Consider firms that are similar in their ability to keep trucks "in use"—demands for outbound "fronthauls" are the same—but differ in their knowledge of backhaul demands. If firms that can match trucks to hauls better absent OBCs are also more likely to adopt OBCs, then $\boldsymbol{\delta}_1$ will overstate OBCs' effect on loaded miles per period in use.

This alternative hypothesis is difficult to examine using methods such as above because the data contain little information about the firm that owns the truck. While I cannot completely rule out this alternative hypothesis, the results below shed some light on its empirical importance. In particular, I will find no evidence of a relationship between OBC use and loaded miles per period in use in 1992. There is thus no evidence that early adopters were firms that were particularly effective in finding backhauls, conditional on the number of periods their trucks were in use; if they were, one would expect to observe a positive relationship between OBC use and loaded miles per period in use in 1992 even if OBCs had no effect on capacity utilization. While I will find a positive relationship between OBC use and loaded miles per period in use in 1997, it is unlikely to reflect that firms that find backhauls efficiently absent OBCs are systematically more likely to adopt OBCs because if it did, one would expect such a relationship to show up in 1992 as well.

In the results section, I will therefore interpret the estimates under the assumption that OBC use is independent of firms' unobserved ability to match trucks to hauls absent OBCs, with the caveat that I cannot rule out interpretations where this assumption holds in 1992 but not 1997.[27]

B. *Heterogeneity in OBCs' Effect*

As noted above, equation (3) assumes away unobserved heterogeneity in OBCs' impact on capacity utilization. In fact, OBCs are likely to affect y_i differently across hauls and be used the most where they have the greatest impact.[28] A more general specification is:

$$\text{(8)} \qquad \ln y_i = \mathbf{X}_i\boldsymbol{\beta} + \boldsymbol{\delta}_{1i}\mathbf{D}_i + \varepsilon_{1i}$$

$$= \mathbf{X}_i\boldsymbol{\beta} + (\boldsymbol{\delta}_1 + \psi_i)\mathbf{D}_i + \varepsilon_{1i}.$$

Here the marginal impact of OBCs on capacity utilization varies with omitted factors. Standard selection issues arise. If $E(\varepsilon_{1i}|\mathbf{D}_i) = 0$, least-squares estimates of the coefficient on $\mathbf{D}_i$ produce the following quantity:

$$\text{(9)} \qquad \hat{\boldsymbol{\delta}}_{1,ls} = \boldsymbol{\delta}_1 + E(\psi_i|\mathbf{D}_i = 1).$$

This coefficient captures the average effect of OBCs among adopters—the average effect of treatment on the treated. Least-squares estimates thus provide the quantities of interest in this paper: OBCs' realized impact on capacity utilization among the trucks for which they have been adopted.

Along with results from basic specifications, below I will report results from specifications that interact the OBC dummies with variables that I observe in the data; these provide estimates of the average returns among adopters within haul characteristic-governance form segments. From equation (9), the average returns among adopters within a segment does not just reflect the mean return to adoption within the segment, but also other moments of the distribution of returns. The average returns among adopters within a segment could be high even if the mean return to adoption is low if there is a large upper tail. I therefore cannot use these estimates to test propositions about cross-segment differences in the average returns to adoption; finding that the estimates are higher in long- than short-haul segments would not necessarily imply that the average returns to adoption increase with haul length. Rather, I will combine these estimates with data on adoption and the distribution of trucks across segments to produce estimates of how the overall returns from OBC adoption are distributed across segments of the industry.

Although it is not the focus of this paper, the results from the interaction specifications will shed some light on the question: how much would OBC use increase capacity utilization for the average truck? I will find no evidence that the average capacity utilization benefits among adopters are positive within some segments. The fact that these benefits appear small or nonexistent among many adopters suggests that they were probably very small among nonadopters as well, especially

[27] Such interpretations would involve a nonmonotonic relationship between firms' unobserved ability to find backhauls absent OBCs and their speed of adoption, since they would require firms adopting by 1992, between 1993 and 1997, and after 1997 to be average, above average, and below average, respectively. There is no indication from trade press accounts that early adopters were worse on this dimension than later ones. Indeed, adoption between 1993 and 1997 sometimes involved exactly the same firms as in the earlier period; these firms adopted OBCs for part of their fleet during the early period, then more of their fleet in the later period.

[28] See Hubbard (2000) for a detailed analysis of adoption patterns.

inframarginal nonadopters. Only about 35 percent of trucks had OBCs as of 1997; hence, OBCs' capacity utilization benefits were probably close to zero for the average truck at this time.

IV. Results

A. *Simple Cross-Sectional Regressions*

Table 2 presents results from univariate cross-sectional regressions that take the form of equation (5).[29] I present these as preliminary to the main results below. The dependent variable is loaded miles. The vector $\mathbf{X}_i$ contains a set of dummy variables that indicate how far from home the truck operated, a set of dummies that indicate what class of trailer was commonly attached to the truck, and dummies that indicate whether trucks were part of private fleets, used for contract carriage, were driven by owner-operators (and if so whether they were operating under long-term arrangements with larger trucking firms), and whether trucks were used to haul "less-than-truckload" shipments. The vector $\mathbf{Z}_i$ consists of a vector of dummy variables that characterize the truck's vintage. The coefficients of interest are those on OBC and EVMS, which correspond to $(\delta_1 + \delta_2)$. OBC is the coefficient on a dummy that equals one if the truck had either a trip recorder or EVMS installed and zero otherwise; EVMS is that on a dummy that equals one if the truck had an EVMS installed and zero otherwise. OBC reflects the correlation between trip recorder use and loaded miles; EVMS reflects the difference in loaded miles for trucks with EVMS and trucks with trip recorders. Thus, OBC picks up relationships between loaded miles and OBCs' incentive- and maintenance-improving capabilities and EVMS picks up those between loaded miles and OBCs' coordination-improving capabilities.

The upper panel contains results using the 1992 data. The specification in the first column restricts all coefficients other than OBC and EVMS to zero, the second estimates the $\mathbf{X}_i$ coefficients but not the $\mathbf{Z}_i$ coefficients, and the third estimates all of the coefficients. From the first column, trucks with trip recorders had 45 percent more loaded miles than those without any IT. Trucks with EVMS had about 29 percent more than those with trip recorders. These estimates decrease sharply when including the controls, and the R^2 increases from 0.04 to 0.48. OBC remains positive and significant, and indicates that controlling for trucks' age and haul characteristics, trucks with trip recorders had 13.3 percent more loaded miles than those without them. Trucks with EVMS had 7.8 percent *fewer* loaded miles than those with trip recorders.

The lower panel reports analogous estimates using the 1997 data. The general patterns are similar to the 1992 data. The estimates in the third column imply that trucks with trip recorders had 7.6 percent more loaded miles than those without them, and that there is no significant difference in loaded miles between trucks with trip recorders and trucks with EVMS.

Estimates from these simple specifications indicate relationships between OBC use and loaded miles, but do not distinguish between

TABLE 2—OBCS AND LOADED MILES: 1992 AND 1997 CROSS-SECTIONAL REGRESSIONS

Dependent variable: ln(loaded miles)			
Panel A: 1992 Sample			
OBC	0.450*	0.203*	0.133*
	(0.025)	(0.022)	(0.021)
EVMS	0.291*	−0.072*	−0.078*
	(0.030)	(0.028)	(0.026)
Controls?	None	**X** vector	**X**, **Z** vectors
R^2	0.044	0.408	0.476
N = 35,766			
Panel B: 1997 Sample			
OBC	0.643*	0.207*	0.076*
	(0.028)	(0.024)	(0.024)
EVMS	0.189*	0.098*	0.024
	(0.028)	(0.025)	(0.025)
Controls?	None	**X** vector	**X**, **Z** vectors
R^2	0.102	0.440	0.495
N = 22,206			

Notes: **X** vector includes distance dummies, trailer dummies, private carriage, contract carriage, independent owner-operator, subcontracted owner-operator, LTL, and LTL × short-haul dummies. **Z** vector includes truck vintage dummies. Eicker-White standard errors are in parentheses.
* Significantly different from 0 at the 5-percent level.

[29] The sample size is lower here than in the previous tables because some observations have missing values for weeks in use.

TABLE 3—OBCS AND LOADED MILES PER PERIOD IN USE:
1997 COEFFICIENT ESTIMATES OF EQUATION (7)—MULTIVARIATE REGRESSIONS

Dependent variables: ln(loaded miles), ln(weeks in use)					
OBC1	0.023	0.019	0.027	0.024	0.032
	(0.029)	(0.030)	(0.029)	(0.029)	(0.029)
EVMS1	0.104*	0.105*	0.094*	0.102*	0.092*
	(0.029)	(0.030)	(0.029)	(0.029)	(0.029)
OBC2	0.056	0.059	0.062	0.047	0.046
	(0.029)	(0.031)	(0.029)	(0.029)	(0.028)
EVMS2	−0.078*	−0.079*	−0.078*	−0.071*	−0.071*
	(0.029)	(0.031)	(0.029)	(0.029)	(0.029)
Lambda (λ)	0.406*	0.387*	0.409*	0.410*	0.412*
	(0.016)	(0.015)	(0.016)	(0.016)	(0.016)
R^2					
Loaded miles equation	0.497	0.497	0.501	0.501	0.505
Weeks in use equation	0.203	0.203	0.203	0.204	0.204
Omits private carriage dummy from **X**?	N	Y	N	N	N
Includes state dummies in **X**?	N	N	Y	N	Y
Includes product dummies in **X**?	N	N	N	Y	Y
N = 22,206					

Notes: OBC1 and EVMS1 measure relationships between OBC use and trucks' loaded miles per period in use. OBC2 and EVMS2 measure relationships between OBC use and the number of periods trucks are in use. Lambda is the estimated elasticity between number of periods in use and number of weeks in use. Eicker-White standard errors are in parentheses.
* Significantly different from 0 at the 5-percent level.

differences in loaded miles per period in use and differences in the number of periods trucks are used. The next subsection reports estimates from multivariate regressions that do so.

B. *Multivariate Regressions*

Table 3 presents GLS estimates of (7) using the 1997 data.[30] $\mathbf{X}_i$ is the same as above. $\mathbf{Z}_i$ includes all of the variables in $\mathbf{X}_i$, plus a full set of truck vintage dummies: if newer trucks are used more weeks than older trucks, this reflects dispatchers' (or the market's) choice of which trucks to use when demand is low.[31] $\mathbf{W}_i$ includes other variables that correlate with the cyclicality of individual trucks' use: dummies that indicate whether the truck was primarily used to haul fresh farm products and live animals. Trucks used to haul these goods are used far fewer weeks than other goods.[32]

The first column contains results from this base specification. OBC1 and EVMS1 are estimates of $\boldsymbol{\delta}_1$, and reflect relationships between OBC use and y_i, loaded miles per period in use. OBC1 is small and not statistically significantly different from zero; this estimate provides no evidence that OBCs' incentive-improving capabilities affect loaded miles per period in use. EVMS1 is positive and significant, suggesting that OBCs' coordination-improving capabilities do so. The point estimate indicates that, controlling for differences in the number of periods differently equipped trucks are used, trucks with EVMS have 10.4 percent more loaded miles than those with trip recorders. Assuming for now

[30] These utilize information from least-squares residuals to produce an estimate of the variance-covariance matrix of the errors in the two equations. While using this as a weighting matrix for systems estimation increases the efficiency of the estimates, in this case doing so has little effect on either the estimates or the standard errors.

[31] Estimates of $\boldsymbol{\delta}_1$ are robust to excluding variables in $\mathbf{X}_i$ from $\mathbf{Z}_i$, in large part doing so does not change which variables are included as controls in the loaded miles equation. See Table A1 for the full set of coefficients from the specifications reported in the first column of Tables 3 and 4.

[32] Preliminary regressions indicated that these variables were correlated with number of weeks in use. The fact that these variables have explanatory power at all is interesting, considering that the unit of observation is a truck-tractor, and truck-tractors are highly mobile and are not specific to firms, trailers, or products outside of the short run. That haul characteristics are significant is evidence of frictions in shifting trucks across uses when demand is low for what they generally haul.

that the orthogonality condition $E(\varepsilon_{1i}|\mathbf{D}_i) = 0$ holds, this is an estimate of the average impact of EVMS' coordination-improving capabilities on loaded miles per period in use among adopters as of 1997. The sum of OBC1 and EVMS1 is 0.127 with a standard error of 0.018. This gives a point estimate of EVMS' total impact on loaded miles per period in use, averaged across adopters: 12.7 percent.

Moving down the table, OBC2 and EVMS2 are estimates of $\boldsymbol{\delta}_2$. These reflect relationships between OBC use and periods in use.[33] OBC2 is positive and EVMS2 is negative. The former is not statistically significantly different from zero using a t-test of size 0.05, but is using one of size 0.15. The latter is significant using one of size 0.05. The point estimates indicate that, holding constant truck vintage and other controls, trucks with trip recorders are used 5.6 percent more periods than trucks without OBCs and 7.8 percent more periods than trucks with EVMS. One interpretation of this is that trip recorders tend to be used for hauls with regular schedules, and these hauls tend not to be cyclical. The sum of OBC2 and EVMS2 is not significantly different from zero, implying that trucks with EVMS are used almost exactly the same number of weeks on the average as trucks without OBCs. While periods in use appears high for trucks with trip recorders, it is not for trucks with EVMS. Controlling for periods in use therefore mostly adjusts for differences between trucks with trip recorders and the other categories, not between trucks without OBCs and with EVMS.

The estimate of λ indicates that doubling the share of periods a truck is in use increases the share of weeks it is in use by about 40 percent.[34] One can strongly reject the hypothesis that this elasticity equals one. As expected, trucks that are in use twice as many weeks are used much more than twice as many periods, and simply normalizing loaded miles by number of weeks in use would not have fully corrected for differences in the number of periods trucks are used.

Comparing the estimates of OBC and EVMS in the right column of Table 2 to those of OBC1 and EVMS1 in Table 3 allows one to observe the effect of the controlling for differences in number of periods in use. Whereas the coefficient on OBC in Table 2 is positive and significant, that on OBC1 in Table 3 is much lower and is not statistically significantly different from zero. In contrast, whereas the coefficient on EVMS in Table 2 is small and not statistically significantly different from zero, that on EVMS1 in Table 3 is positive and significant. Ignoring the fact that the trucks with trip recorders are used more periods than other trucks leads one to overstate OBCs' incentive benefits and understate their coordination benefits.

The rest of the columns report results from specifications that provide evidence regarding whether the potential biases from reverse causation and spurious correlation discussed above are economically significant. These thus examine the assumption $E(\varepsilon_{1i}|\mathbf{D}_i) = 0$. The second column omits the private carriage dummy from $\mathbf{X}_i$; if the estimate of EVMS1 in the first column reflects that EVMS adoption is high where loaded miles per period is high because of differences in drivers' service responsibilities, omitting the private carriage dummy should exacerbate this bias and cause the coefficient to increase. However, the estimate of EVMS1 is almost exactly the same as in the first column, increasing by a very small and statistically insignificant amount. The rest of the columns include in $\mathbf{X}_i$ a full set of state, product, and state and product dummies, respectively. The coefficients on these dummies themselves, not reported here, are jointly significant; this provides evidence that loaded miles per period in use varies with the products trucks haul and the state in which they are based. However, the estimates of OBC1 and EVMS1 are almost exactly the same as in the first column, particularly those in the last column that contain the full set of controls. This provides evidence that the estimates of OBC1 and EVMS1 in the first column do not reflect the effect of spurious correlation related to unobserved congestion or logistical sophistication. If they did, one would expect OBC1 and EVMS1 to decrease when

[33] Multiplying these by the estimate of λ provides estimates of relationships between OBC use and weeks in use.

[34] In specifications not shown here, I have estimated the model holding λ constant at values between 0.3 and 0.5—a range 20 times the standard error—and find that the estimates of OBC1 and EVMS1 are stable within this range. Also, the estimates change little when allowing λ to be a function of $\mathbf{X}_i$.

TABLE 4—OBCs AND LOADED MILES PER PERIOD IN USE: 1992 COEFFICIENT ESTIMATES OF EQUATION (7)—MULTIVARIATE REGRESSIONS

Dependent variables: ln(loaded miles), ln(weeks in use)					
OBC1	−0.011	−0.027	−0.010	−0.009	−0.008
	(0.027)	(0.028)	(0.027)	(0.026)	(0.027)
EVMS1	0.022	0.048	0.013	0.027	0.017
	(0.032)	(0.033)	(0.032)	(0.031)	(0.032)
OBC2	0.144*	0.159*	0.143*	0.137*	0.137*
	(0.027)	(0.028)	(0.027)	(0.026)	(0.026)
EVMS2	−0.100*	−0.123*	−0.100*	−0.096*	−0.096*
	(0.029)	(0.031)	(0.027)	(0.029)	(0.028)
Lambda (λ)	0.431*	0.409*	0.432*	0.436*	0.438*
	(0.011)	(0.010)	(0.012)	(0.011)	(0.012)
R^2					
Loaded miles equation	0.476	0.476	0.480	0.484	0.488
Weeks in use equation	0.191	0.190	0.191	0.192	0.192
Omits private carriage dummy from **X**?	N	Y	N	N	
Includes state dummies in **X**?	N	N	Y	N	Y
Includes product dummies in **X**?	N	N	N	Y	Y
N = 35,766					

Notes: OBC1 and EVMS1 measure relationships between OBC use and trucks' loaded miles per period in use. OBC2 and EVMS2 measure relationships between OBC use and the number of periods trucks are in use. Lambda is the estimated elasticity between number of periods in use and number of weeks in use. Eicker-White standard errors are in parentheses.
* Significantly different from 0 at the 5-percent level.

including these additional controls. In sum, the robustness of the estimates to the inclusion or exclusion of these controls provides evidence that biases related to unobserved haul characteristics discussed above are likely quite small.[35]

The results in Table 3 thus provide evidence that OBC adoption has increased capacity utilization in trucking through better resource allocation decisions. Taking the coefficients as point estimates of the benefits to adopters, EVMS increased loaded miles per period in use among trucks for which they were adopted by an average of 12.7 percent. Using the means in Table 1, this translates to about 8,200 more loaded miles per truck per year: about one more medium-distance haul per week. Alternatively, one can think of this as about five fewer hours per 40-hour week of empty or idle time. Most of this increase was due to EVMS' coordination-improving capabilities; point estimates indicate that they increased capacity utilization among adopters by an average of 10 percent. In contrast, Table 3 provides no evidence that OBCs' incentive- and maintenance-improving capabilities increased loaded miles per period in use. Trucks with trip recorders do have higher loaded miles than those without them, but this appears to be due mainly to differences in the number of periods they are used—possibly due to the regularity of the hauls—rather than the effects of technology.

Table 4 contains analogous estimates using the 1992 data. The first column contains estimates from the base specification. Strikingly, the estimates of OBC1, EVMS1, and (OBC1 + EVMS1) are all small and not statistically significant. In contrast to the 1997 estimates, these estimates provide no evidence that OBCs increased loaded miles per period in use among adopters as of 1992. The estimates of OBC2 and EVMS2 show similar patterns to 1997, but are greater in absolute value. They indicate that trucks with trip recorders were used 14.4 percent more periods than those without OBCs and 10.0 percent more than those with EVMS. Comparing these estimates to those in the right column of Table 2 indicates that, as in 1997, ignoring differences in periods in use leads one

[35] More generally, it indicates that any important failure of the orthogonality condition $E(\varepsilon_{1i}|\mathbf{D}_i) = 0$ would have to be due to unobserved haul or firm characteristics that are not strongly correlated with geographic regions, product differences, or drivers' service responsibilities.

to overstate OBCs' incentive effect and understate their coordination effect on capacity utilization.

The rest of the columns report results from specifications that omit and exclude variables as before. In the second column, I omit the private carriage dummy. Unlike in the 1997 data, the EVMS1 estimate increases substantially and the OBC1 estimate decreases somewhat, as one would expect under the reverse causation story addressed earlier. This provides evidence that the estimates in the first column may reflect the effect of unobserved differences in drivers' jobs as well as any causal effects. But since OBC1 and EVMS1 were not statistically significantly different from zero in the first place, this does not change the conclusion that there is no evidence that OBCs increased loaded miles per period among adopters during 1992. The rest of the columns include the state, product, and state and product dummies, respectively. Like in the 1997 data, the estimates in the first column are robust to the inclusion of these dummies, indicating that once again, it is unlikely that they reflect spurious correlations related to unobserved differences in congestion or recipients' logistical sophistication.

Thus, Table 4 provides no evidence of OBC-related increases in loaded miles per period in use as of 1992, roughly four to five years after the first OBCs appeared on the market. Contrasting this with the 1997 results, the fact that the average returns among adopters increase over time is inconsistent with a simple "moving down the demand curve" diffusion story where the highest return adopters adopt first and appropriate the benefits instantaneously, but is consistent with interpretations where the benefits of adoption come with a lag.

Lags in the returns to technology adoption are believed to be common by some economists, even for some very important innovations.[36] Though not the focus of this paper, interviews with dispatchers and other industry participants provide some candidate explanations for such lags in this context. One is that improvements in dispatching software throughout the 1990's enabled dispatchers to utilize the information OBCs collect better. For example, software presented truck location information in graphical (i.e., on a map) rather than text format, and this made it easier for dispatchers to use this information to forecast trucks' availability and match them to hauls. Another is that, software improvements aside, it took time for dispatchers and firms to learn how to use the new information OBCs provided effectively. Evidence from the trade press provides further support for this point. For example, Jim Mele (1993) reports that while advanced OBCs were initially "accepted as alternatives to telephones that allowed drivers to make check-in calls without leaving their trucks ... some fleets are beginning to exploit the real potential that comes from ... taking information from vehicles and feeding it directly into management systems to make the best possible decisions on dispatching and load matching." Given this observation, made in early 1993, it is unsurprising to find far more evidence of OBC-related capacity utilization increases in 1997 than 1992.

C. *Heterogeneity in the Returns to Adoption*

Table 5 reports 1997 estimates from analogous specifications that allow the OBC and EVMS coefficients to vary across 12 cells. These cells are distance/trailer/governance permutations; each coefficient therefore reflects a three-way interaction. Short-haul trucks include those that generally operate less than 50 miles from their base; long-haul trucks are those that generally operate more than 50 miles from their base.[37] These estimates provide evidence regarding whether the returns to adopters vary in the sample according to variables I observe. The left panel reports a specification where I estimate all of the model's coefficients; the right panel reports results when I restrict all of the OBC1 coefficients to zero.

The table shows two general patterns. First, with the exception of the common/van/short cell, any evidence that OBCs' incentive-improving capabilities lead to increases in capacity utilization is weak. None of the other OBC1 coefficients are statistically significantly different

[36] See Paul A. David (1990) and Timothy F. Bresnahan and Shane Greenstein (1996) for discussions of lags in the returns to adoption in the context of electrification and computers, respectively.

[37] I have estimated the models dividing the long-haul cells more finely. The results are similar to those below.

TABLE 5—OBCS AND LOADED MILES PER PERIOD IN USE: 1997 COEFFICIENT ESTIMATES OF EQUATION (7)—MULTIVARIATE REGRESSIONS ESTIMATES OF OBC1 AND EVMS1 FOR TRAILER-DISTANCE-GOVERNANCE CELLS

	Unrestricted specification		OBC1 = 0	
	Short haul	Long haul	Short haul	Long haul
OBC1				
Private, van	−0.062	0.055		
	(0.132)	(0.065)		
Private, not van	0.124	−0.054		
	(0.262)	(0.089)		
Contract, van	−0.149	0.001		
	(0.620)	(0.057)		
Contract, not van	−0.019	0.119		
	(0.485)	(0.059)		
Common, van	0.600*	−0.064		
	(0.156)	(0.065)		
Common, not van	−0.415	0.152		
	(0.218)	(0.087)		
EVMS1				
Private, van	0.462*	0.116	0.404*	0.161*
	(0.172)	(0.067)	(0.148)	(0.047)
Private, not van	−0.081	0.147	0.028	0.094*
	(0.281)	(0.095)	(0.127)	(0.055)
Contract, van	0.375	0.097	0.225	0.097*
	(0.631)	(0.52)	(0.189)	(0.036)
Contract, not van	0.422	−0.103	(0.398)	−0.001
	(0.469)	(0.055)	(0.236)	(0.052)
Common, van	−0.223	0.280*	0.364*	0.228*
	(0.156)	(0.066)	(0.103)	(0.042)
Common, not van	0.556	−0.020	0.152	0.116*
	(0.323)	(0.093)	(0.308)	(0.054)
Log of likelihood function	−40,009		−40,015	

Notes: OBC1 and EVMS1 measure relationships between OBC use and trucks' loaded miles per period in use. Specifications are analogous to those in Table 3. Eicker-White standard errors are in parentheses.

* Significantly different from 0 at the 5-percent level.

from zero. Furthermore, one can reject the null that the OBC1 coefficients are jointly equal to zero using a likelihood ratio test of size 0.05.

Second, the estimates indicate that the average returns among adopters from OBCs' coordination-improving capabilities differ across segments. Moving to the right panel, the EVMS1 coefficients are statistically significantly different across cells. There are two notable patterns when comparing the estimates across governance forms. One is that the coefficients in the private carriage cells are similar to their counterparts in the common carriage cells; in fact, one cannot reject the null hypothesis they are the same. This is interesting because many private fleet dispatchers are constrained with respect to the extent that they can match trucks to the demands of external customers; such constraints would lower the returns to adoption, averaged across the entire segment. If so, the fact that average returns among private carriage and common carriage adopters are similar suggests heterogeneity in the returns among private fleets. One interpretation of the results is that some private fleet dispatchers are relatively unconstrained, and EVMS helps them improve capacity utilization in the same way it helps for-hire fleet dispatchers. The other pattern is that there is less evidence of OBC-related capacity utilization increases in the contract carriage cells than the other cells. The coefficient on EVMS1 is positive and significant only in the contract/van/long cell, and the coefficient in this cell is statistically significantly lower than its counterpart in the common/van/long cell. This

TABLE 6—DISTRIBUTION OF EVMS-RELATED CAPACITY UTILIZATION INCREASES, 1997

Column	(1)	(2)	(3)	(4)	(5)	(6)
Label	Coefficient estimate	Share of industry	EVMS adoption	Share × EVMS adoption	Industry CU gains from cell	Share of CU gains
Formula				(2) × (3)	(1) × (2) × (3)	
All trucks	0.127	1.000	0.256	0.256	0.033	1.000
Private, van, short	0.404	0.027	0.151	0.004	0.002	0.048
Private, not van, short	0.028	0.118	0.070	0.008	0.000	0.007
Contract, van, short	0.225	0.009	0.100	0.001	0.000	0.006
Contract, not van, short	0.398	0.007	0.158	0.001	0.000	0.013
Common, van, short	0.364	0.019	0.146	0.003	0.001	0.029
Common, not van, short	0.152	0.017	0.094	0.002	0.000	0.007
Private, van, long	0.161	0.146	0.310	0.045	0.007	0.209
Private, not van, long	0.094	0.182	0.166	0.030	0.003	0.081
Contract, van, long	0.097	0.135	0.444	0.060	0.006	0.166
Contract, not van, long	−0.001	0.086	0.294	0.025	−0.000	−0.001
Common, van, long	0.228	0.161	0.343	0.055	0.013	0.361
Common, not van, long	0.116	0.094	0.237	0.022	0.003	0.074

Notes: "All trucks" coefficient estimate is (OBC1 + EVMS1) from the first column in Table 3. Cell coefficient estimates are from the right panel of Table 5. Share of industry is the cell's share of trucks. EVMS adoption is the share of trucks in the cell that have EVMS installed. Share of CU gains is the cell's share of industrywide OBC-related increases in loaded miles per period in use.

indicates that the distribution of the returns to adoption differs between these cells, and is consistent with the interpretation that schedule regularity tends to make the capacity utilization-related returns uniformly low within contract carriage. OBCs are sometimes installed on trucks used for hauls governed by long-term arrangements, but more of the benefits probably come in ways other than truck utilization; for example, it may enable shippers' customers to allocate resources better by helping them track and anticipate deliveries.

Table 6 explores the distribution of EVMS-related capacity utilization increases. The first row reports the estimate of (OBC1 + EVMS1) from the first column in Table 3 (0.127), followed by several calculations. Reading across, the "all trucks" cell is 100 percent of the industry, EVMS adoption in this cell is 25.6 percent, and adopters in this cell make up 25.6 percent of the industry. Taking 12.7 percent as the average capacity utilization increase among adopters in the industry, these imply that EVMS use by adopters in this (universal) cell increased capacity utilization by 3.3 percent. This is an estimate of advanced OBCs' effect on capacity utilization in the industry as of 1997.

The rest of the rows use the estimates from the right panel of Table 5 to investigate how the 3.3 percent capacity utilization increase splits across trailer/distance/contractual form cells. For example, the EVMS1 coefficient in the private/van/short cell is 0.404. This cell made up 2.7 percent of the industry and adoption was 15.1 percent in this cell. Thus adopters in this cell made up 0.4 percent of the industry and on the average increased capacity utilization by 40.4 percent. Adoption within this cell increased capacity utilization in the industry by 0.17 percent (0.404 × 0.004), which is 4.8 percent of the industry total. Although the average returns among adopters are high within this cell, there are so few adopters in this cell that it contributes a small amount to the overall capacity utilization increase.

The main result from this table is that the distribution of IT-related productivity increases appears highly skewed across segments. Only 5.5 percent of the trucks in the industry—adopters in the common/van/long cell—account for about 36 percent of the capacity utilization increase.[38] Approximately another 37 percent comes from the other two long-haul van cells.

[38] For all rows save the first, column (6) equals column (5) divided by 3.48 percent, which is the sum of the column (5) entries from the cells. This differs from 3.25 percent, the estimate of industry capacity utilization gains from Table 3, because the coefficient estimates in column (1) are from a different specification.

Thus, about 15 percent of the U.S. fleet accounts for about 73 percent of the benefit. More than half of the rest comes from adopters in the long-haul nonvan cells.

D. *How Much of the Increase in Capacity Utilization Between 1992 and 1997 Was EVMS-Related?*

The estimates in Table 3 imply that EVMS enabled increases in capacity utilization of the U.S. tractor-trailer fleet of 3.3 percent in 1997. In contrast, there is no evidence from Table 4 that they led to significant increases in capacity utilization as of 1992. Table 1 reported that loaded miles per truck increased by 10.1 percent between 1992 and 1997. The point estimates in this paper suggest that about 33 percent of this increase (0.033/0.101) was related to the growing use of on-board computers to achieve better matches between trucks and hauls. A substantial part of the rest is likely due to the expansion of the economy during this time.

This estimate of 33 percent should probably be considered an upper bound, because EVMS use may have led to capacity utilization increases within certain segments as of 1992. Table A2 in the Appendix shows 1992 results from specifications analogous to Table 5. In the right panel, the estimates of EVMS1 are positive and significant for the private/not van/long and common/van/long cells. These point estimates indicate that adoption within these cells increased capacity utilization fleetwide by 0.4 percent.[39] If one assumes that capacity utilization increases are zero in the rest of the cells, this would imply that about 29 percent [(0.033–0.004)/0.101] of the capacity utilization increase between 1992 and 1997 was due to EVMS-related improvements in resource allocation.

E. *What Are the IT-Enabled Increases in Capacity Utilization Worth?*

Trucking makes up a significant part of the economy; thus, even small proportional increases in productivity imply large benefits in absolute terms. The American Trucking Associations estimates that trucking (including private fleets) was a $486 billion industry in 1998, or 6.1 percent of GDP.[40] Operating margins are small in trucking; therefore, this is a rough approximation of costs. Multiplying $486 billion by 3.3 percent gives a back-of-the-envelope estimate of the value of OBC-related increases in capacity utilization: $16 billion per year. This estimate does not account for productivity benefits other than in truck utilization, such as any benefits that accrue to shippers and receivers from being better able to anticipate trucks' arrivals. Sixteen billion dollars in annual benefits therefore may well be a conservative estimate for the general productivity gains associated with OBC use as of 1997.

These increases in capacity utilization have involved costs, but the costs are probably very small relative to the benefits. Although there are depreciation and labor costs from using trucks more intensively, these are probably quite small in many cases. For example, running trucks loaded rather than empty causes little extra depreciation, and does not require drivers to work more hours. Furthermore, the OBCs themselves are very inexpensive; the most popular EVMS costs users only $100 per month per truck to lease, including messaging costs. While my point estimate of the average capacity utilization increase among adopters is 13 percent, EVMS hardware and messaging costs increase operating costs by less than 1 percent.[41] Finally, while using OBCs effectively usually requires some complementary investments in human capital and back-office IT, it generally does not involve changes in dispatchers' or drivers' jobs that require significant amounts of training, and backoffice hardware and software is usually PC based and supplied by competitive firms. The net benefits would be very high even if the

[39] Adopters within these two cells made up 0.88 percent and 4.01 percent of the fleet, respectively; $0.004 = (0.0088 \times 0.160 + 0.0401 \times 0.097)$.

[40] American Trucking Associations (2000). I quote the estimate for 1998 because methodological changes and new data led this and other publications to substantially increase their estimate of the size of the industry, starting first with estimates for 1998. These methodological changes account for the fact, for example, that much of "rail" and "air" freight travels by truck for all or part of the way.

[41] Assuming operating costs of $2/mile (American Trucking Associations, 2000) and 6,000 miles per truck per month, average monthly operating costs are on the order of $12,000 per month.

amortized cost per truck of these complementary investments were five times hardware and messaging costs, and there is no indication from interviews and the trade press that the costs associated with such investments are nearly this large.

V. Conclusion

Technologies that collect and disseminate information play a unique role in the economy. As Hayek stated more than 50 years ago, such technologies increase productivity by improving *decisions,* in particular resource allocation decisions. This paper examines the impact of one such technology—on-board computers—on capacity utilization in the trucking industry. The evidence in this paper indicates that on-board computer use has increased capacity utilization significantly: in 1997, EVMS increased capacity utilization by 13 percent on adopting trucks. This increase appears to be mostly due to advanced capabilities that let dispatchers determine trucks' position in real time, and allow dispatchers and drivers to communicate while drivers are in their trucks. These capabilities enable dispatchers and drivers to keep trucks on the road and loaded more.

On-board computers in trucking are among the first commercially important applications of wireless networking technologies. Many other such applications are likely to follow in the near future, as companies are currently attempting to develop and commercialize wireless applications that work off a diverse set of hardware platforms, including phones and handheld computers. The economic value of these applications is based on the same principle as OBCs: information improves decisions; communication enables decisions to be executed. This allows dispersed individuals to identify and avail themselves of economic opportunities. The estimates in this paper indicate that the productivity gains from such applications can be quite large.

TABLE A1—OBCs AND LOADED MILES PER PERIOD IN USE: 1992 AND 1997 COEFFICIENT ESTIMATES OF EQUATION (7)—MULTIVARIATE REGRESSIONS

		1997		1992	
Dependent variables: ln(loaded miles), ln(weeks in use)		Estimate	Standard error	Estimate	Standard error
δ vector	OBC1	0.023	0.029	−0.011	0.027
	EVMS1	0.104*	0.029	0.022	0.033
	OBC2	0.056	0.029	0.144*	0.027
	EVMS2	−0.078*	0.029	−0.100*	0.029
β vector	C	10.037*	0.041	10.008*	0.033
	Area: 50–100 miles	0.178*	0.046	0.264*	0.031
	Area: 100–200 miles	0.454*	0.046	0.527*	0.033
	Area: 200–500 miles	0.753*	0.046	0.778*	0.031
	Area: >500 miles	1.009*	0.043	0.993*	0.031
	Private carriage	−0.118*	0.024	−0.134*	0.022
	Contract carriage	0.086*	0.022	0.091*	0.019
	Owner-operator: Independent	0.216*	0.061	0.117*	0.033
	Owner-operator: Subcontractor	0.264*	0.038	0.239*	0.032
	Trailer: Lowboy	0.023	0.066	0.029	0.052
	Trailer: Platform	0.031	0.033	0.023	0.026
	Trailer: Refrigerated van	−0.021	0.027	0.002	0.024
	Trailer: Logging	0.474*	0.070	0.277*	0.044
	Trailer: Grain body	0.533*	0.085	0.475*	0.063
	Trailer: Dump	0.363*	0.046	0.359*	0.037
	Trailer: Tank	0.034	0.037	0.011	0.029
	Trailer: Other	−0.113*	0.033	−0.208*	0.026
	LTL	−0.091*	0.029	−0.082*	0.028
	LTL × (area < 50)	−0.161*	0.080	−0.405*	0.056
γ vector	C	–	–	–	–
	Area: 50–100 miles	0.466*	0.055	0.316*	0.035
	Area: 100–200 miles	0.486*	0.054	0.338*	0.036
	Area: 200–500 miles	0.444*	0.052	0.300*	0.034
	Area: >500 miles	0.305*	0.051	0.196*	0.034
	Private carriage	−0.176*	0.027	−0.230*	0.023
	Contract carriage	−0.027	0.025	−0.063*	0.020
	Owner-operator: Independent	−0.298*	0.084	−0.114*	0.039
	Owner-operator: Subcontractor	−0.231*	0.045	−0.163*	0.036
	Trailer: Lowboy	−0.512*	0.083	−0.656*	0.060
	Trailer: Platform	−0.147*	0.039	−0.159*	0.029
	Trailer: Refrigerated van	0.097*	0.034	0.076*	0.026
	Trailer: Logging	−0.264*	0.088	−0.090*	0.047
	Trailer: Grain body	−0.958*	0.100	−0.789*	0.077
	Trailer: Dump	−0.138*	0.056	−0.213*	0.043
	Trailer: Tank	0.013	0.039	0.011	0.032
	Trailer: Other	−0.051	0.036	0.006	0.025
	LTL	0.024	0.033	−0.015	0.026
	LTL × (area < 50)	0.599*	0.086	0.463*	0.052
	Model year 1996 (1991 for 1992 specification)	0.229*	0.028	0.375*	0.025
	Model year 1995 (1990 for 1992 specification)	0.202*	0.027	0.415*	0.023
	Model year 1994 (1989 for 1992 specification)	0.154*	0.029	0.339*	0.023
	Model year 1993 (1988 for 1992 specification)	0.118*	0.031	0.288*	0.025
	Model year 1992 (1987 for 1992 specification)	0.114*	0.035	0.241*	0.026
	Model year 1991 (1986 for 1992 specification)	0.029	0.036	0.146*	0.027
	Model year 1990 (1985 for 1992 specification)	−0.070*	0.039	0.094*	0.028
	Model year 1989 (1984 for 1992 specification)	−0.076*	0.037	0.044	0.029
	Model year 1988 (1983 for 1992 specification)	−0.190*	0.041	0.006	0.038
	Model year 1987 or before (1982 for 1992 specification)	−0.643*	0.033	−0.529*	0.027
α vector	Farm products	−0.174*	0.018	−0.185*	0.016
	Live animals	−0.190*	0.038	−0.179*	0.022
λ		0.406*	0.016	0.431*	0.011

Note: Standard errors are Eicker-White.
 * Significantly different from 0 at the 5-percent level.

TABLE A2—OBCs AND LOADED MILES PER PERIOD IN USE: 1992 COEFFICIENT ESTIMATES OF EQUATION (7)—MULTIVARIATE REGRESSIONS ESTIMATES OF OBC1 AND EVMS1 FOR TRAILER-DISTANCE-GOVERNANCE CELLS

	Length of haul		Length of haul	
	Short	Long	Short	Long
OBC1				
Private, van	0.674*	−0.145*		
	(0.327)	(0.040)		
Private, not van	−0.004	0.007		
	(0.202)	(0.061)		
Contract, van	0.015	−0.085		
	(0.236)	(0.043)		
Contract, not van	−0.356	−0.112		
	(0.391)	(0.066)		
Common, van	0.426	−0.100		
	(0.297)	(0.075)		
Common, not van	−0.266	0.323*		
	(0.172)	(0.075)		
EVMS1				
Private, van	−0.673	0.158*	−0.048	0.043
	(0.405)	(0.065)	(0.259)	(0.060)
Private, not van	−0.385	0.153	−0.390*	0.160
	(0.263)	(0.103)	(0.139)	(0.089)
Contract, van	−0.271	0.108	−0.256	0.031
	(0.487)	(0.054)	(0.447)	(0.040)
Contract, not van	0.443	−0.057	0.104	−0.158*
	(0.412)	(0.114)	(0.169)	(0.098)
Common, van	−0.120	0.189*	0.296	0.097*
	(0.410)	(0.077)	(0.290)	(0.035)
Common, not van	0.247	−0.499*	−0.002	−0.201*
	(0.194)	(0.115)	(0.139)	(0.092)
Log of likelihood function	−68,183		−68,219	

Notes: OBC1 and EVMS1 measure relationships between OBC use and trucks' loaded miles per period in use. Specifications are analogous to those in Table 3. Eicker-White standard errors are in parentheses.

* Significantly different from 0 at the 5-percent level.

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